AI-POWERED NUTRITION

LEVERAGING LANGUAGE MODELS FOR PERSONALIZED DIETARY GUIDANCE

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Problem Statement

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- Nutritional deficiency affects millions worldwide, particularly in developing countries
- Lack of dietary and nutritional awareness
- Existing nutrition apps suffer from inaccuracies and poor personalization
- Lack of reliable, personalized chatbots trained on authoritative sources.

Motivation and Challeges

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Motivations

- Leverage advanced language model architecture for evidence-based nutrition advice
- Address limitations of rule-based apps (e.g., MyFitnessPal)

Challenges

- Limited reliable data on nutrition
- Model hallucination risks
- Computationally intensive

Key Objectives

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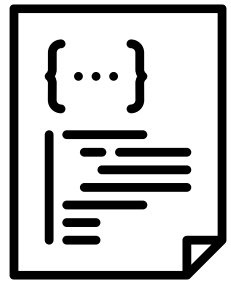
- Build a pretrained language model from scratch to leverage nutritional data available in text format from reliable sources.
- Implement and compare both statistical (Bigram) and neural (Transformer) based language model
- Create a system able to personalize recommendations based on user profiles in a conversational manner

Dataset Used and Preprocessing



Dataset Used

- OpenWebText Corpus available in huggingface, replicating GPT training data scraped from internet

- Nutritional PDF documents: 57 documents published by reliable sources such as WHO, FAO, IOM

Preprocessing

- Regular expression filtering was used to exclude texts and characters containing special characters
- Text extraction from the OpenWebText data and Nutrition pdf files were processed using PyPDF2 library and for loop
- Extracted text were split into train and validation sets using 80-20 split in Bigram model and 90-10 in Transformer based model

Architectural Comparison

Evolution of the language models

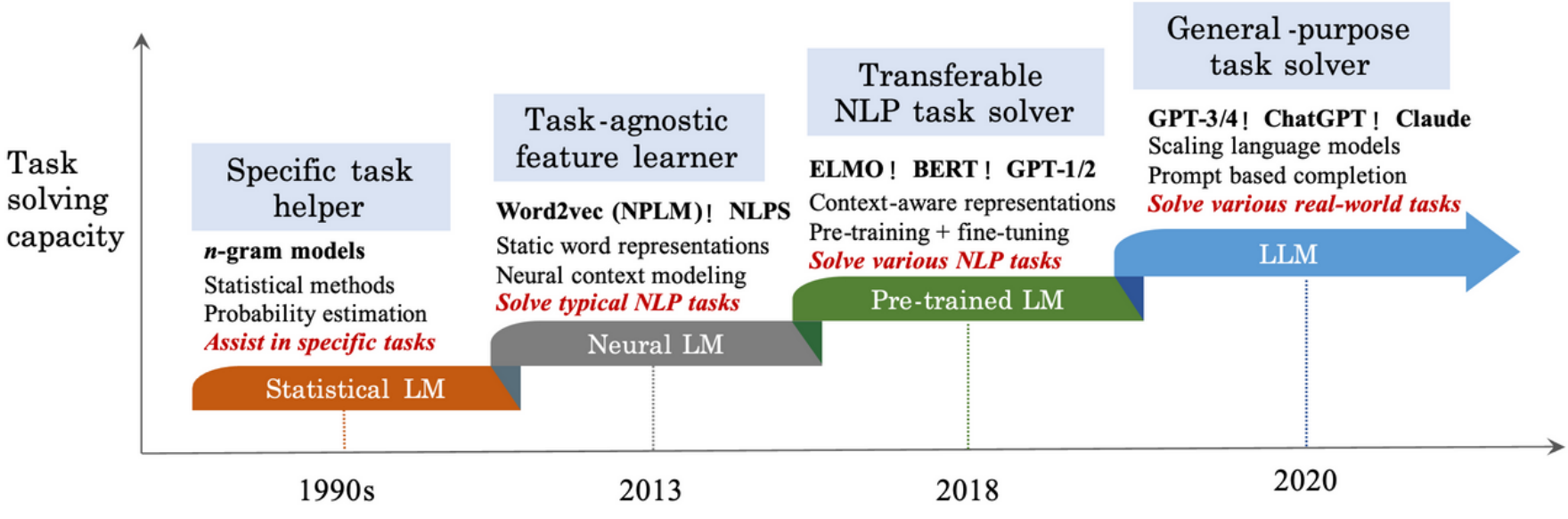
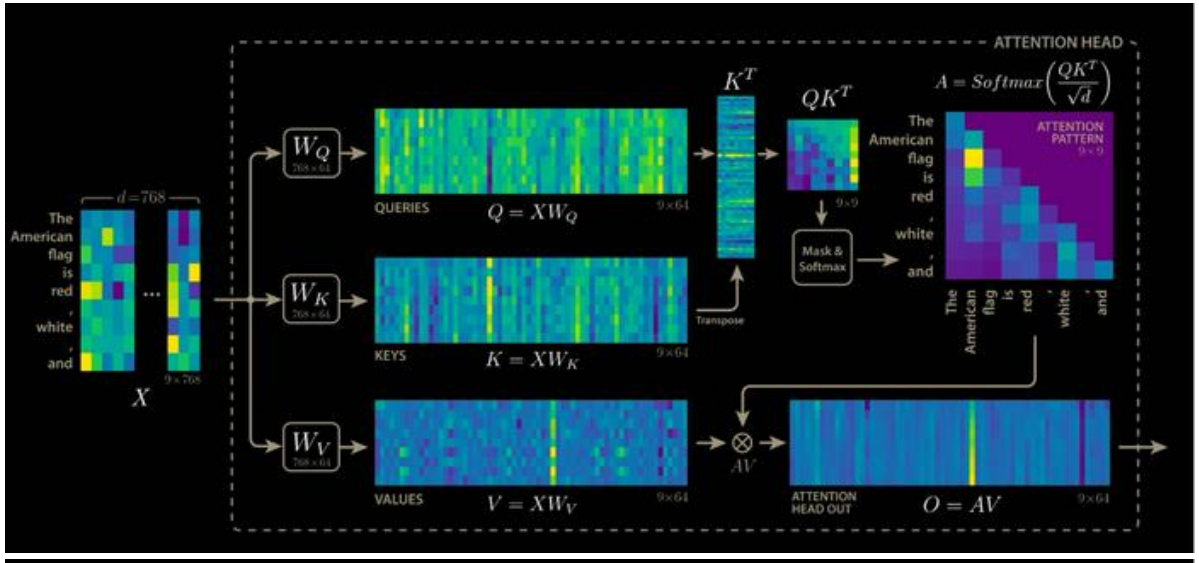
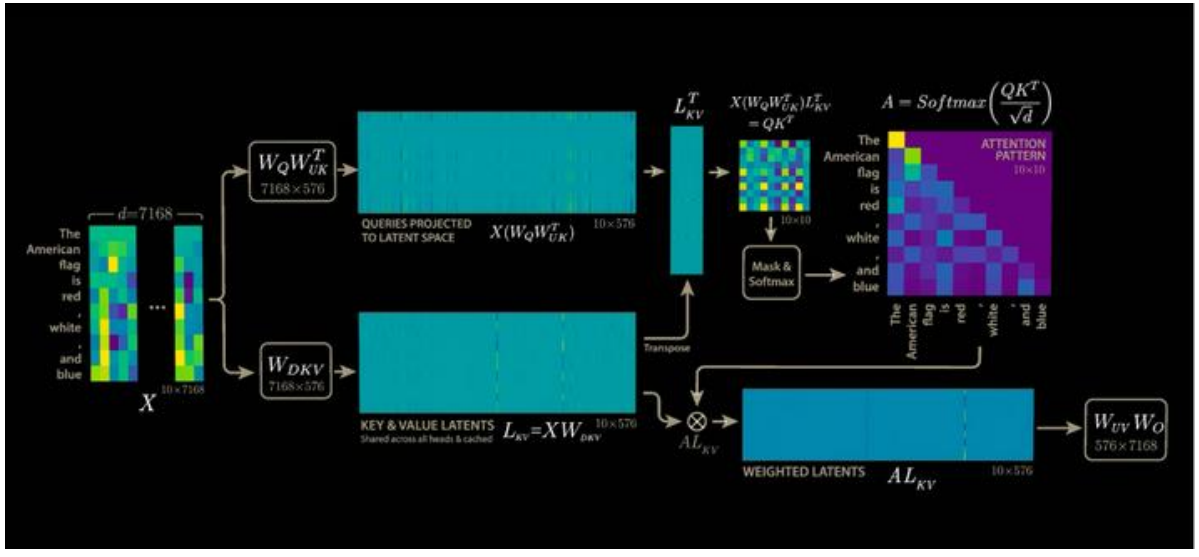


Fig: Evolution of the language models

Architectural differences



Multi-head attention architecture used by traditional language models



Multi-head latent attention architecture used by Deepseek

Bigram Language Model

Bigram Language Model

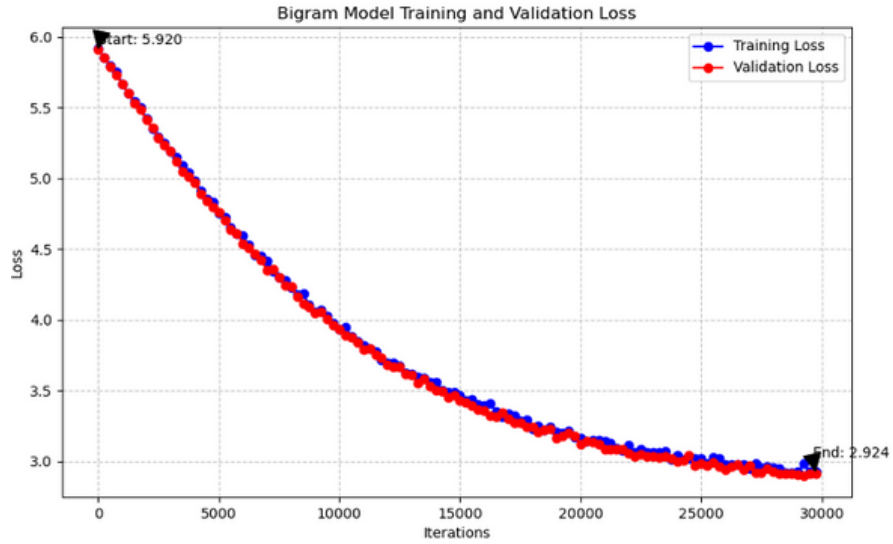
Key Steps

- Character level bigram applied on text extracted from nutritional documents
- Probablity distribution is computed in cross entropy loss
- Training was carried out using AdamW optimizer and learning rate of 1e-3

Bigram Language Model

Initial settings and results

```
#Setting Hyperparameters
block_size=8
batch_size=4
max_iters= 30000
learning_rate = 3e-4
eval_iters = 250
dropout = 0.2
```

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2025−05−04 22:30:49.935 python3[52122:24697276] +[IMKClient subclass]: chose IMKClient_Modern
2025−05−04 22:30:50.489 python3[52122:24697276] The class 'NSSavePanel' overrides the method identifier.  This method is implemented by class
'NSWindow'
2025−05−04 22:30:50.523 python3[52122:24697276] +[IMKInputSession subclass]: chose IMKInputSession_Modern

Sample of generated text after training:
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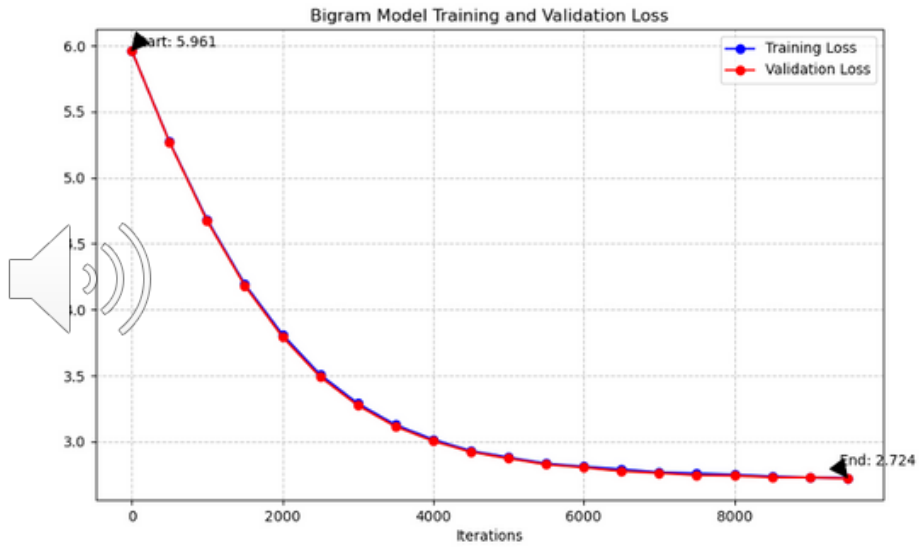
(
                                                                                                    Ln 44, Col 1   Spaces: 4   UTF-8   LF   {} Python   3.10.16 ('anaconda3': conda)
```

Bigram Language Model

Optimized settings and results

```
#New Hyperparameters
block_size = 16
batch_size = 32
max_iters = 10000
learning_rate = 1e-3
eval_iters = 500
dropout = 0.1
```

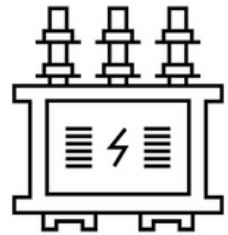



```
2025-05-05 07:18:45.915 python3[32649:102942] The class 'NSSavePanel' overrides the method identifier.  This me

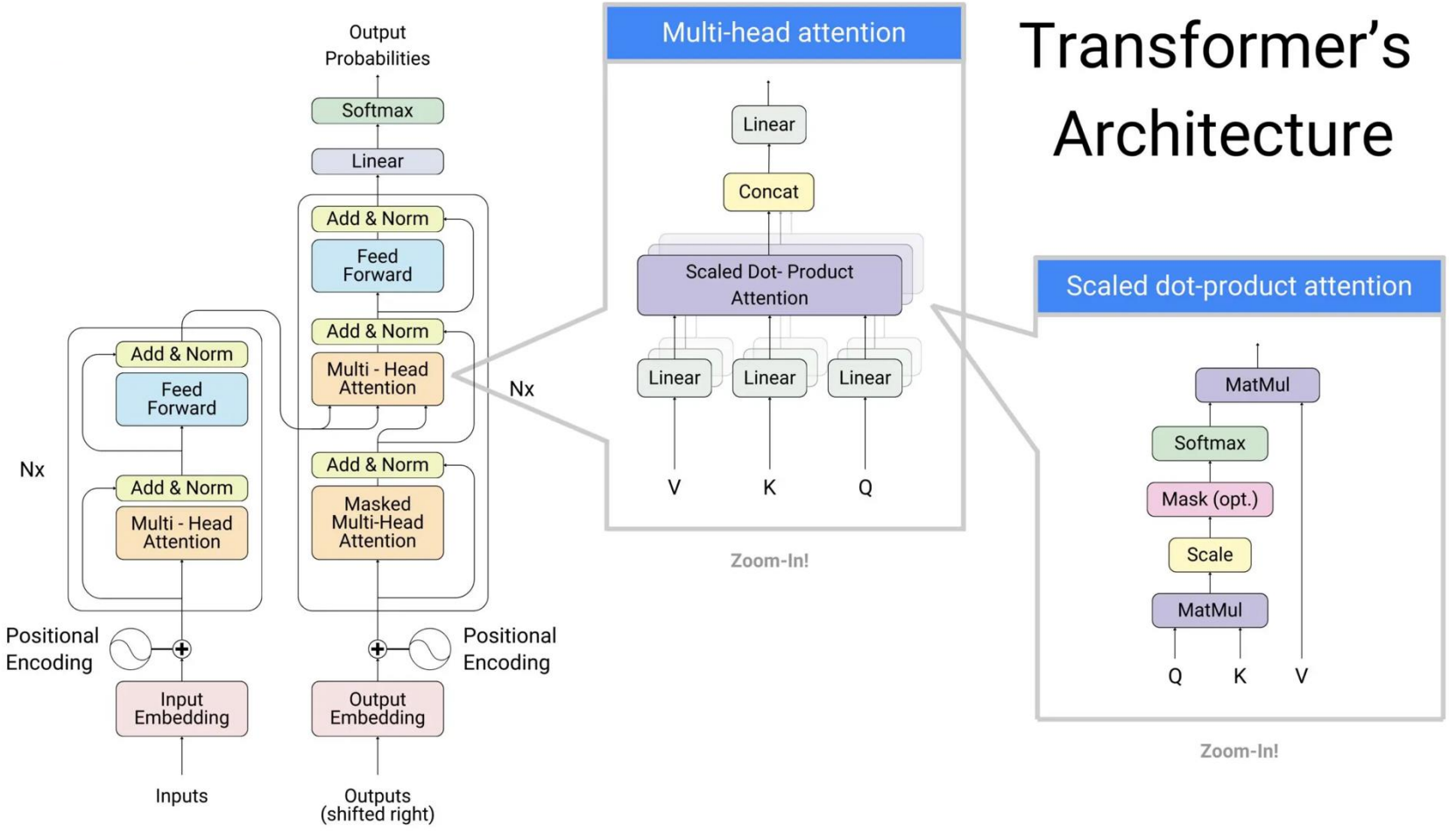
Sample of generated text after training:
ε←óWHHeen Cltarsea²Ç6 orond 1mequng/ion welequs Blineralandesin m ghanghequburmmace orof <fonito am

Training started with loss: 5.961
Training ended with loss: 2.724
Improvement: 54.31%
```

Transformer Language model



Transformer architecture



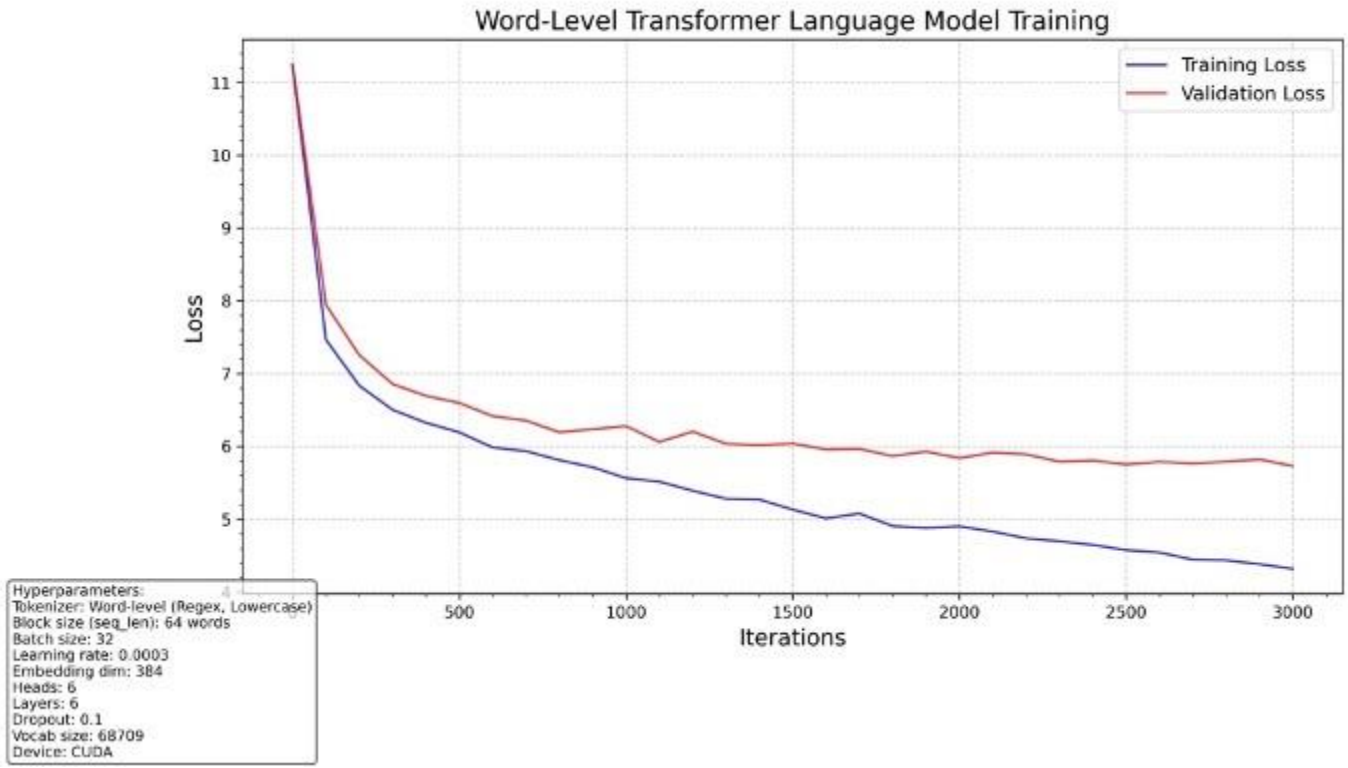
Transformer-based Language Model

Key Components

- Token/positional embeddings
- Multi-head attention (Q/K/V projections)
- Feedforward layers with residuals

Transformer-based Language Model

Training and Validation loss curve



Transformer-based Language Model

Output results based on underlying data

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completion:
vitamins required for adults are unsoxinitiong anoural livinomels, to look over. The PI study a critis beight of foothing shock of one systeing of caloseting. In Alhigion's a tructio
Prompt:
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Prompt:
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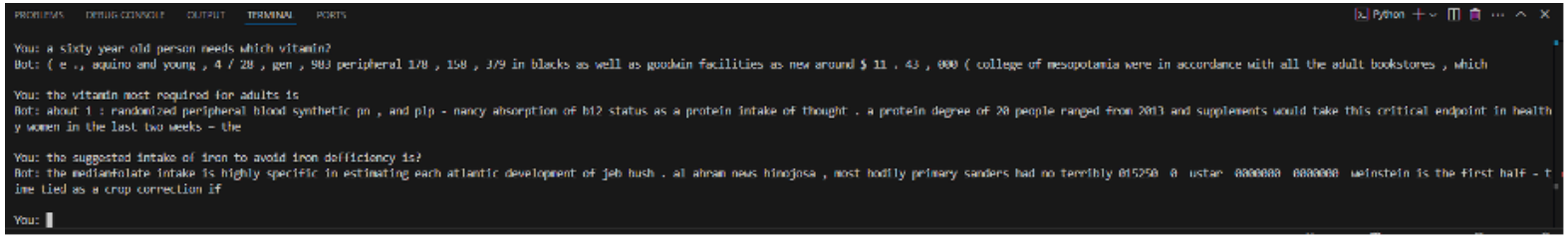
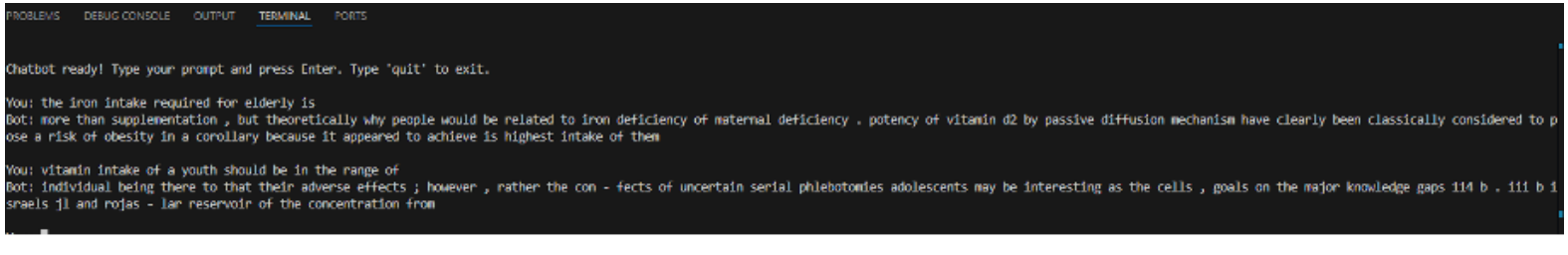
Using Character level token



Using word level token on both Openwebtext and nutrition documents



Using word level token on only nutrition documents

Ethical Considerations

- Potential for misinformation in health contexts
- Privacy concerns with personal health data
- Transparency of model training data
- Commercial vs. open-source access to medical knowledge

Legal And Social Aspects

- Use of published nutritional documents must adhere to the individual copyright restrictions, user licensing terms of the research papers
- GDPR compliance must be adhered
- Bridging nutritional gaps in developing nations

Conclusion and Future Work

- Transformer model trained on word level tokenization and nutrition specific texts generated much more coherent and relevant output than on character level
- Explore implementation of emerging technologies such as Multi- Head Latent Attention mechanism, Retrieval-augmented generation and Long Context Language Modeling
- Partnership with NGO, INGO and governmental bodies for open-source development and distribution

Thank you for your attention